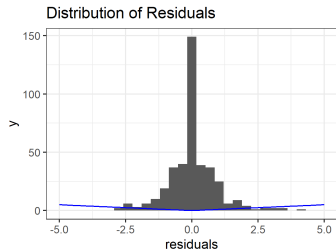


Introduction to Machine Learning

Maximum Likelihood Estimation vs. Empirical Risk Minimization



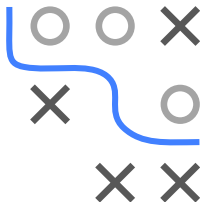
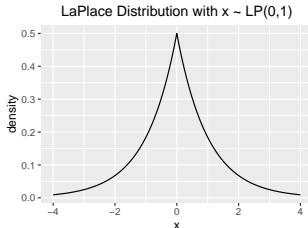
Learning goals

- Correspondence between Laplace errors and L1 loss
- Correspondence between Bernoulli targets and the Bernoulli / log loss

LAPLACE ERRORS - L1-LOSS

Let's consider Laplacian errors ϵ now, with density:

$$\frac{1}{2\sigma} \exp\left(-\frac{|\epsilon|}{\sigma}\right), \sigma > 0.$$



Then

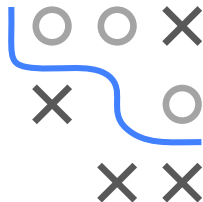
$$y = f_{\text{true}}(\mathbf{x}) + \epsilon$$

also follows Laplace distrib. with mean $f(\mathbf{x}^{(i)} | \boldsymbol{\theta})$ and scale σ .

LAPLACE ERRORS - L1-LOSS

The likelihood is then

$$\begin{aligned}\mathcal{L}(\boldsymbol{\theta}) &= \prod_{i=1}^n p\left(y^{(i)} \mid f\left(\mathbf{x}^{(i)} \mid \boldsymbol{\theta}\right), \sigma\right) \\ &\propto \exp\left(-\frac{1}{\sigma} \sum_{i=1}^n \left|y^{(i)} - f\left(\mathbf{x}^{(i)} \mid \boldsymbol{\theta}\right)\right|\right).\end{aligned}$$



The negative log-likelihood is

$$-\ell(\boldsymbol{\theta}) \propto \sum_{i=1}^n \left|y^{(i)} - f\left(\mathbf{x}^{(i)} \mid \boldsymbol{\theta}\right)\right|.$$

MLE for Laplacian errors = ERM with L1-loss.

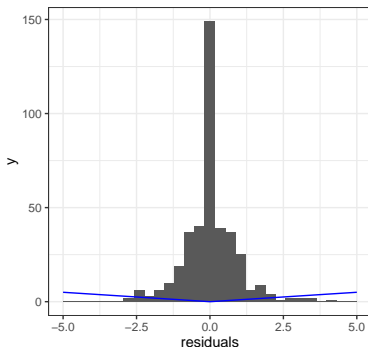
- Some losses correspond to more complex or less known error densities, like the Huber loss [► Meyer, 2021](#)
- Huber density is (unsurprisingly) a hybrid of Gaussian and Laplace

LAPLACE ERRORS - L1-LOSS

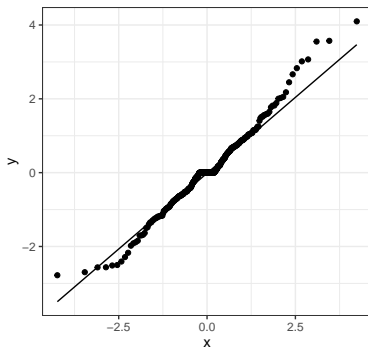
- We simulate data $y \mid \mathbf{x} \sim \text{Laplacian}(f_{\text{true}}(\mathbf{x}), 1)$ with $f_{\text{true}} = 0.2 \cdot \mathbf{x}$.
- We can plot the empirical error distribution, i.e. the distribution of the residuals after fitting a regression model w.r.t. L_1 -loss.
- With the help of a Q-Q-plot we can compare the empirical residuals vs. the theoretical quantiles of a Laplacian distribution.



Distribution of Residuals



Residuals vs. Quantiles of Error Distribution



MAXIMUM LIKELIHOOD IN CLASSIFICATION

This gives rise to the following loss function

$$L(y, \pi(\mathbf{x})) = -y \log(\pi(\mathbf{x})) - (1 - y) \log(1 - \pi(\mathbf{x})), \quad y \in \{0, 1\}$$

which we introduced as **Bernoulli** loss.

